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Modelling the location and spatial pattern of a crop boom. A case study from Laos

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ABSTRACT

Crop booms are phenomena of global environmental change that keep on occurring around the globe and frequently exploit or degrade the local socio-ecological resources (resulting in e.g. loss of biodiversity, soil erosion, indebtedness). While causal mechanisms were identified and summarized in several frameworks, the causal effects of the identified factors remained largely unknown. In this study, we set up a new application of a spatial land system model to examine the causes for the clustered spatial pattern of the maize boom between 2000 and 2016 in Sayaboury Province, Laos. The factors tested included market access (travel time to trader companies), land productivity and total net revenue (proxy for profitability), spatial differences in farm gate price of maize, slope, and soil types. While crop booms are commonly associated with high commodity prices and improved market accessibility, our simulation results suggested that the combination of the geographic and economic factors we tested partially contribute to explain the location and spatial extent of the maize boom, but a full explanation has not been found. Interestingly though, temporal dynamics, such as increases in land productivity and profitability had the largest effect on model performance regarding the size of the maize boom area (experiment 2). Productivity and profitability increased thanks to political economic support for the introduction of a series of techniques (i.e. hybrid maize cultivars, herbicides, mechanical tillage and sowing) that made maize mono-cropping disproportionally competitive over other land management. We outline implications of our findings for governance bodies that are faced with crop booms.

1. Introduction

Crop booms induce fast land use changes in which export-oriented crops such as maize, cassava, rubber or oil palm expand within a short period of time and dominate landscapes in the form of monocultures (Hall, 2011). In statistical records, this becomes visible as sharp surges of production or area of highly demanded commodities. For example, the area cultivated with cassava increased more than tenfold in Cambodia from 30.000 to 350.000 hectares between 2005 and 2010 (FAOSTAT). Likewise, maize production in the Lao PDR (Laos) rose sixfold in the same time period from 200.000 to 1.200.000 tonnes (FAOSTAT). These crop booms are generally not uniformly distributed nationwide; they concentrate in certain locations. As the notion of 'boom' suggests, local production quickly rises but falls too, i.e. they go 'bust'. Crop booms have happened many times in the past and continue to appear and disappear in different places around the globe. In earlier centuries, crop booms have occurred with the development of colonial plantations (Byerlee, 2014). More recently, investments by both large agribusinesses and smallholder farms are driving rapid agricultural expansion and intensification at the cost of forests and fallow areas (Byerlee, 2014; Cramb et al., 2015; Friis et al., 2016; Manivong and Cramb, 2008).

The causes of crop booms and their respective land use changes are complex and several factors come together at the same time in specific places (Mahanty and Milne, 2016). Case studies from Cambodia, Laos and Myanmar have shown that the locations where recent crop booms

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occurred, have several contextual factors in common (Byerlee, 2014). They include high rates of poverty and loose or ambiguous land governance in forest margins. In these places known as ‘forest frontiers’ (Barney, 2009; Peluso and Lund, 2011), the large gap in labor cost and land prices relative to more developed locations constitutes a pull factor which is often used for political and economic purposes to attract investors and migrants with the aim to stimulate economic growth and to assert government control over the territorial margins.

The consequences of crop booms include farming systems that rely on mono-cropping with associated loss of biodiversity and carbon storage, declining soil fertility, soil erosion. Given the strong specialization, the local agricultural communities become vulnerable to price fluctuations, and indebtedness due to lack of own capital by most smallholders for farm inputs. This in turn leads to inequality within local societies among those who ‘make it’ and those who were unlucky or failed to benefit financially from the boom at the right time (Bruun et al., 2017; Lestrelin et al., 2012; Mahanty and Milne, 2016; Rigg and Vandergeest, 2011). In short, crop booms are repetitive social, environmental and economic transformations that keep on occurring at high speed and magnitude and are caused by a combination of factors.

The speed and complex nature of crop booms are challenges to governance bodies that try to both stabilize forested areas with associated biodiversity and at the same time foster economic growth of agrarian societies. This is the case in several tropical countries, for example in Laos, where the reduction of poverty and protection of natural resources has been the underlying goal of land tenure reforms for decades (Ducourtieux et al., 2005; Lestrelin, 2010). Once the phenomenon takes on momentum, it becomes very difficult to convince the increasing number of stakeholders who benefit from the crop boom, to stop engaging in it. Consequently, understanding the combination of factors that causes crop booms could be used to identify areas where policies need adaptation to help preventing negative consequences on local livelihoods and limit associated deforestation and land degradation.

Two dimensions of causality need to be considered to arrive at robust causal explanations for specific land use changes: both an understanding of the causal mechanisms and evidence for the causal effect of single factors are necessary (Meyfroidt, 2016). Causal mechanisms line out how factors combine in a process to influence the outcome [i.e. land use] (Meyfroidt, 2016)and they are often presented in the form of conceptual frameworks. Causal effects are necessary to mathematically formalize the relationships between the elements within the frameworks, and to build models with less uncertainty for a better understanding of land use change.

There is a rich body of literature on the causal mechanisms behind crop booms in Southeast Asia, particularly from a viewpoint of political ecology and political economy. Five recent studies identify key factors and suggest frameworks to explain the emergence of crop booms. We group their findings into economic, political, social and environmental dimensions (Table 1). Hall (2011) suggests that smallholders, large agribusinesses and state actors are not only driven by the opportunity of profit, but also by the opportunity of control over land. He proposes to use the concept of powers of exclusion that involves powers of markets (incl. speculation), regulation, legitimization and force (Peluso and Lund 2011). Byerlee (2014) analyzed several historical and contemporary crop booms using a framework of three main factors that enable crop booms: economic fundamentals, biased economic policies and the belief in high modernism of certain forms of agricultural production and technology (e.g. for agricultural intensification). Cramb et al. (2015) compared different boom crops to examine which agro-economic factors support smallholder engagement. They found that a key favouring condition is the availability of upstream (e.g. seeds, chemical inputs) and downstream services (e.g. transport, marketing) by intermediaries who can broker between a large number of smallholders and other agribusinesses in the market value chain. Mahanty and Milne (2016) argue that key factors co-occurred in the cassava

Table 1
Factors in the causal mechanisms suggested by studies on crop booms in Southeast Asia.

Study	Economic factors	Political and Political-economic factors	Social factors	Environmental Resources
Hall 2011 Processes of taking control over land by diverse stakeholders	Market powers via price (purchase, selling, leasing, contract schemes)	Regulation and Force Regulation: who should practice which land use Force: violence	Legitimization With arguments for the wellbeing of state, region, population	Frontier areas and core agricultural production areas, Timber on concession land
Byerlee 2014 Enabling factors for plantations and/or smallholders engaging in crop booms	Economic fundamentals High commodity price, pioneering costs, processing facilities	Biased (local) economic policies towards a group of agricultural stakeholders; Large agribusinesses supported by access to cheap land and labour Smallholders: supported by extension services and programs that foster new technologies (machinery, crop varieties, chemical inputs) for agricultural intensification	High modernism belief	Frontier areas
Cramb et al. 2015 Agro-economic factors favouring smallholder engagement	Embedding of smallholders in functioning value chain upstream: production inputs, planting material, finance & knowledge downstream: transportation, processing and marketing	Public agencies & intermediaries that broker between smallholders and agribusinesses		Land already reasonably cleared, i.e. annually cropped fields or fallow fields
Mahanty & Milne 2016 Drivers of cassava boom Cambodia	Market demand, material property of crop (e.g. low efforts to plant cassava)	Overlapping and contradictory policies and laws, subject to change and reinterpretation	Connectivity and transborder networks	Resource abundance: unguarded forestland, timber ripe for harvest, initial fertility of soil

(continued on next page)

Table 1 (*continued*)

Study	Economic factors	Political and Political-economic factors	Social factors	Environmental Resources
Ornetsmüller et al. 2018a Key decision factors for smallholders to engage in maize boom	Market demand for boom crop (i.e. trader offering contract) Profitability Feasibility (labor, knowledge, capital) Lack of competitive alternative	Agricultural expansion by smallholders in their own village onto fallow land that is under customary land rights. National policies discourage use of this land for shifting cultivation practices	Underlying motivation: family aspirations, improving wellbeing, education, housing, imitation behavior	Availability of land perceived: communal fallow and forestland

boom of Cambodia, including strong market demand, the ease of growing cassava, overlapping and contradictory governance, trans-border networks and the abundance of land resources. Finally, Ornetsmüller et al. (2018a) found that, from a smallholder farmer's perspective, mainly market availability (i.e. demand), profitability and feasibility stimulate adoption and expansion of boom crops in a situation where farmers perceive that enough land is available to expand into (mostly fallows and communal land). While Hall (2011) refrains from prioritizing which factors are most important, Byerlee suggests that local political economies which are biased towards large plantations enabled the most recent booms in the early 21st century. Ornetsmüller et al. (2018a) mention that favorable economic factors were essential for smallholders in the context of lacking, competitive alternatives for boom crops. All of them state, that a notion of 'enough available land', often in frontier areas forms the environmental context, partly explaining the location of crop booms from a view at regional and global scale.

The different authors have described how crop booms typically occur. However, the hypotheses, stemming from analysis of empirical evidence have not yet been tested with independent data. In other words, it is unknown whether the (combination of) factors mentioned in the frameworks have causal effects and if so, how strong they are. A variety of spatio-temporal data is needed to be able to explain, and maybe to predict, the location of a crop boom. Relevant datasets become more and more accessible, yet, they often are incomplete, fragmented and cover only a part of the spatial extent or temporal resolution needed.

Land use models are frequently applied tools to explore land use dynamics and their structure can be seen as a representation of the theoretical understandings of the system studied (Meyfroidt et al., 2018). Irwin and Geoghegan (2001) differentiate in their review between structural economic land use models and geographic, spatially explicit land use models. The latter type can help examining hypotheses about the location of crop booms in a counterfactual approach, i.e. testing the effect of specific factors one by one in a laboratory-like experiment. Some factors, such as the terrain and other bio-physical factors, are broadly contextual and easy to represent in spatial allocation models, while other processes and variables are more difficult to include. Current large-scale, spatially explicit land use models have limitations in representing the system as described by Verburg et al. (2015). Amongst these, the representation is human agency in regional models is the most frequent discussed limitation (see Rounsevell et al., 2012, 2014 and Müller-Hansen et al., 2017). For example, most models are shaped by questions from a top-down, institutional view and related to food security, export volumes etc., in terms of production of crops in tons that can be generated per land unit. However, from a perspective of smallholder farmers who recently entered cash-cropping contracts with traders, decisions on how to use their land are more oriented to expected monetary income (Ornetsmüller et al., 2018a). Furthermore, many computer models work with extrapolation of trends and projections and have difficulty in capturing processes like crop booms that constitute abrupt land use regime shifts (Müller et al., 2014).

The objective of this study is to analyze the causal effects of economic, geographic and policy factors on the spatial pattern of a crop boom in Southeast Asia. We focus on the province of Sayaboury in Laos as a case, where smallholders recently engaged in a boom of hybrid maize which is exported as fodder to the growing livestock industries of Thailand, Vietnam and China. Using a spatial land use model like a laboratory, we aim to test a selected set of factor combination(s) to see whether they have an effect on the location and spatial pattern of the maize boom and how strong these effects are.

The remainder of this paper is structured as follows. We first introduce the context of the study area in Laos. Then, the iterative modelling approach and model choice is outlined before we explain in-depth how we parameterized the baseline model, designed and implemented three experiments and how the outcomes of the simulation

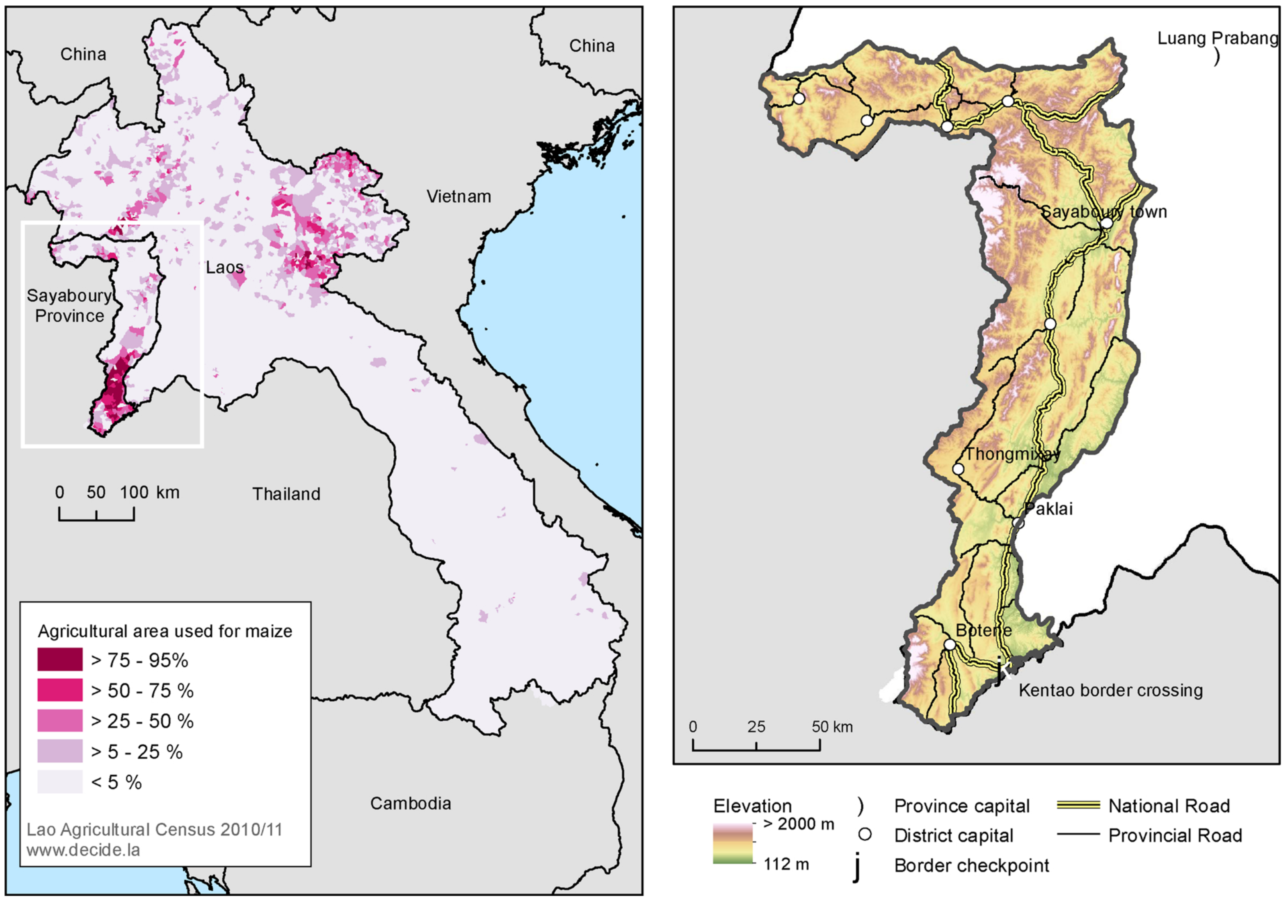

Fig. 1. Study area: Sayaboury Province, Laos.

are evaluated against a reference map. The results section presents the main findings of both the baseline model and the experiments. Finally, we discuss the results against the backdrop of literature, data limitations and give an outlook on future research needs.

2. Methodology

2.1. Study area

We analyzed a boom of hybrid maize cultivation by smallholder farmers in Sayaboury Province, northern Laos at the border to Thailand (Fig. 1). The study area covers 16,389 km^2 of land area and according to the population census of 2015, approximately 381,000 people live in the province.

In this section we describe the broader (national) economic, political, social and environmental situation that reflects the categories of Table 1 and give an account of the land use history of the study area.

Economically speaking, Laos is characterized as low-income country with relatively high poverty rates. It has long been on the global list of least developed countries but recently graduated from this status in 2018 (UN, 2018). Poverty rates declined from 30% in 2005 (Epprecht et al., 2008) to 24.6% in 2011 (LSB, 2016). Yet, in comparison to Thailand and other emerging Southeast Asian countries such as China and Vietnam, there is still a considerable gap in monetary household income, illustrated by the trend to seasonal work migration in order to send remittances back to Laos, particularly in areas close to the borders (see e.g. Manivong et al., 2014). In Sayaboury Province, which is considered a highly productive agricultural 'basket' within Laos, more than 80% of the population rely in their livelihoods on farming, earlier in subsistence but increasingly engaged in commercial agriculture (Thanichanon, 2015). For smallholders, market access particularly in remote areas is organized via contract farming schemes in which the trader offers upstream services of the value chain (seeds, chemical inputs, credit etc) and downstream services (transport, processing, storage and marketing). Consequently, a contract offered by traders equals market demand in the perception of farmers (Ornetsmüller et al. 2018a).

Laos is governed by a post-socialist, one-party communist government in which all land belongs to the people (i.e. the state). Land use policies such as the Land and Forest Allocation LFA program have aimed at alleviating poverty while protecting forests with a combination of land zoning, prohibiting the use of forestland for agricultural purposes (incl. shifting cultivation, a traditional agro-forestry practice) and granting tenure security when farmers adopt intensive farming practices (Ducourtieux et al. 2005). While these policies have proven ineffective in many parts of the country and neither led to land sharing nor land sparing (Ducourtieux et al. 2005, Vongvisouk et al., 2016a), intensive, hybrid maize cropping was promoted yet again as 'green economic growth' under the Eighth five-year National Socioeconomic Development Plan 2016-2020 (Kallio et al. 2019). Land administration is weak in protecting forests against agricultural expansion; local authorities provide permits if land is used to grow maize while upland rice cropping (i.e. shifting cultivation) gets restricted and comes with insecure land rights (Kallio et al. 2019).

Socially, the improved living standards, possibilities for education, land tenure security and road access that come along with cash cropping are much desired (Ornetsmüller et al., 2018a; Thanichanon, 2015). A maize-monument was mounted in Paklai town, illustrating how maize became an icon for development and how a large part of the population welcomed and respected the crop at its beginning and in peak times. Often, pioneer farmers tried out the crop and when successful, the majority of other households in the village followed

(Ornetsmüller et al., 2018a). Culturally and economically Sayaboury Province is oriented towards Thailand as the four southern districts were part of Thailand during the second world war and still today the Thai baht remained as currency (Laffort and Dufumier, 2006).

Environmentally, Laos is rich in forests, biodiversity and water and perceived as such by its neighbouring countries, which makes these natural resources a geopolitical asset in the political ecology and political economy of the Lao Government (see e.g. Creak and Barney, 2018; Lestrelin et al., 2013; Matthews, 2012; Mills, 2017). However, forest cover declined from 49% in the early 1980ies to 40% in 2010 while the government's target for 2020 is to reach 70% forest cover (Fujita and Phanvilay, 2008; Vongvisouk et al., 2016b).

The land use history of Sayaboury Province was important for the design of this study. Before the year 2000, agricultural land was mostly used for paddy rice on flat terrain, especially in valley bottoms, and rotational upland crops on the hillsides (i.e. a kind of shifting cultivation with short fallow cycles, 2 to 3 years). Rotational cropping systems included a mix of different crops such as upland rice, chili, banana, etc. and some traditional maize to feed local livestock. In this area of Laos, a single harvest per crop type per year is common. In 2003, the first hybrid maize varieties (LVN 10 and CP888, see Keil, 2010) were introduced together with herbicides. Weeding was labor intensive and restricted the amount of land a household could manage. In 2005 the first motorized ploughing services were introduced. Consequently, less labor was necessary to control weeds and the cropped area per household rose from one to three hectares. The farmers re-invested parts of the profits they gained from hybrid maize in these years to pay for earth works of excavators in order to expand paddy rice areas (Ornetsmüller et al., 2018a). Around the year 2009-2010, soil fertility had declined and mineral fertilizers were necessary in order to keep up the yields of maize (Lestrelin et al., 2012; Thanichanon, 2015). Meanwhile, storage facilities and mechanized sowing became available. However, continuing land degradation and the fall of farm gate prices for maize after 2010 made it less and less profitable. Health issues arised for the farmers who applied herbicides and many smallholders diversified their practices or even fully abandoned maize cropping around 2015-2016 (Lestrelin et al., 2012; Ornetsmüller et al., 2018a; Thanichanon, 2015).

We selected this province for our study as it was the first area in the country where the maize boom took place and datasets from different sources and qualities were available that provided a basis for a first modelling study. Even though the boom happened mostly in the southern part of the province, we chose to build a model application for a larger extent (the whole province) for analytical reasons. To know whether a factor combination is explaining the right location of the boom, there needs to be an opportunity for the model to simulate a wrong location. By doing so, we allowed falsifiability of the hypotheses.

2.2. Modelling approach

Different types of land use models have been developed over the past decades for different purposes and objectives, ranging from economic models that focus on land use decision making based on market prices and costs to spatial models that emulate changes in spatial patterns based on neighbouring land uses (Brown et al., 2013; Irwin and Geoghegan, 2001). To explore the geographic question on the effects of factors contributing to the location of crop booms, we used the CLUMondo modelling framework (Van Asselen and Verburg, 2013) which is based on a geographic approach and spatially allocates diverse types of demands on the land ranging from agricultural commodities, to various ecosystem services (Stürck et al. 2015), water for irrigation (Malek and Verburg, 2017) and biodiversity protection and carbon sequestration (Eitelberg et al., 2016). A key difference to other frameworks is that CLUMondo simulates land systems (i.e. socio-ecological systems) instead of land cover/land use and that it relates multiple demands to multiple land system types (LS) instead of a one to one relationship as found in many other geographic land use/land cover models (Ornetsmüller et al. 2016; Van Vliet and Verburg, 2018). The main components necessary and used in this study include a land system classification, suitability maps per land system class, specification of demand types and amount of demand per year aggregated on a regional level, supply estimates for each land system, conversion rules and competitive advantage estimates. The model iteratively allocates the land systems with the highest transition potential at a certain time and location (i.e. land system pixel), whereas the transition potential is calculated as the sum of suitability, conversion resistance and competitive advantage (Debonne et al. 2018). More in depth explanations of the model framework can be found in Debonne et al. (2018), Van Asselen and Verburg (2013) and Van Vliet and Verburg (2018).

We selected this model as it suits the purpose and objective of this study for the following reasons. First, it simulates spatial allocation of land use which is necessary to answer the research question regarding the location and spatial pattern of the maize boom in Sayaboury Province. Second, it can be parameterized to consider different types of demands on the same land simultaneously (Van Vliet and Verburg, 2018) and mimic choices and competitiveness between different land use options. Third, CLUMondo can model land systems, i.e. complex landscape mosaics that are prevalent in the study area, such as rotational cropping (shifting cultivation) (Van Asselen and Verburg, 2013). Fourth, CLUMondo allocates land uses to pixels with the highest transition potential i.e. it models utility maximization. While there is a variety of underlying beliefs and values to decision making of Lao farmers, the maximization approach fits well with the dynamics of decision making during a boom. The lucrative opportunity of cash cropping is tempting and followed by a majority of farmers as the 'get rich quick stories can seem compelling' (Hall 2011). Fifth, in the perception of farmers, demand comes from 'outside', i.e. Thailand, Vietnam, China. In the model, demand is also exogenously defined in an aggregate way.

In order to operationalize the causality tests for land use simulation, we defined crop booms as a spatially clustered pattern of land systems, that contain boom crops in more than half of the agriculturally used area e.g. more than 50% of agricultural land is occupied with maize. Furthermore, a crop boom is characterized by a spatio-temporal boom and bust pattern, i.e. rapid increase and decrease of land systems dominated by the boom crop.

2.3. Model parameterization

To parameterize a baseline version of the model for Sayaboury Province, we first collected and processed all data needed. Then we iteratively designed three model simulation experiments in a counterfactual approach, i.e. a new experiment is designed after the results of the previous model simulation are known.

The components to parameterize a baseline version of the model included a land system classification, suitability maps, inter- and extrapolated estimates of the market demands for the whole study area based on several data points of the time 2002-2016, the productivity (i.e. supply) of each land system, relative competitiveness of each land system, conversion resistance and conversion rules to represent the possible land use trajectories.

2.3.1. Land system classifications

A land use map is one of the basic inputs to the model. However, conventional land use and land cover (LUCC) classifications do not represent the typical land uses in the study area, such as rotational cropping (i.e. short-fallow shifting cultivation). Also, LUCC maps contain coarse categories such as 'agricultural land' which usually lack information about specific crops. To solve this issue and locate where maize dominates, we adopted a land systems approach and developed two new land system classifications. Land systems (LS) are units to describe typical socio-ecological features of a landscape in order to

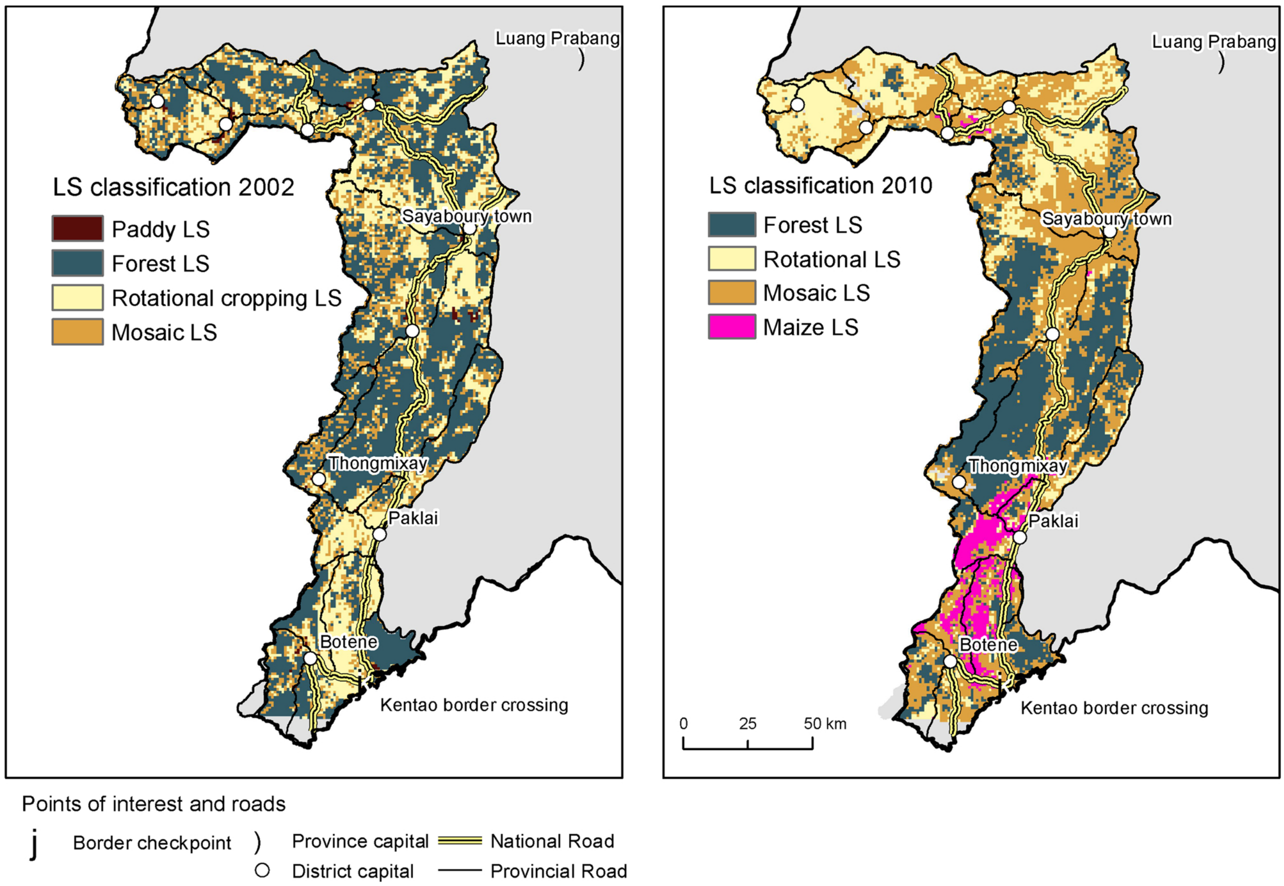

Fig. 2. Land system classifications 2002 and 2010. Rotational cropping is a form of shifting cultivation with shortened fallow cycles.

represent the diversity of land management practices (such as shifting cultivation) that are invisible on land cover classifications (Letourneau et al., 2012; Ornetsmüller et al., 2018b; Van Asselen and Verburg, 2012). The approach includes merging official land cover classifications and agricultural censuses at village level of the Government and a more detailed account of the approach, the data and decision trees are given in Supplementary Appendix A. The resulting land system (LS) classifications each differentiate four LS categories respectively at a pixel size of 1 x 1 km or 100 ha (Fig. 2). The LS classification 2002 includes paddy LS, forest LS, rotational LS and mosaic LS. The LS classification 2010 includes forest LS, rotational LS, maize LS and mosaic LS. They cover different categories because maize LS only emerged after 2002 and paddy was not traceable in 2010 because of a lack of this feature in the land cover classification 2010. Both classifications however complement each other as inputs to the model and can therefore aid in specifying the land systems that occurred/changed during this period of transition in Sayaboury Province.

2.3.2. Suitability maps based on logistic regression

Suitability maps are also a core input to the CLUMondo land system model as they describe the probability of a land system to occur at a certain location. The suitability maps are calculated using logistic regression equations that relate an existing land use pattern (LS classification) as the dependent variable to a number of independent, biophysical and socioeconomic factors. First, we collected and preprocessed a set of socioeconomic and biophysical variables that on the one hand are often used for land use models such as slope, soil types, precipitation, temperature, elevation, general accessibility or population density (Alcamo et al., 2006). On the other hand, we selected and prepared spatial datasets that would make it possible to test hypotheses specific to the study area: market access represented by accessibility to trader companies versus access to province capital, district capital or the border checkpoint to Thailand. Also the difference between village accessibility by larger, official national roads and small roads could be included in the pool of potential explanatory variables. A full list is given in Supplementary Appendix B, Table B1, whereas those marked with an sterix remained after the regression procedure explained in the following.

Subsequently, we took randomized training and test samples of each LS and independent variables. Accounting for correlation among independent variables (Pearson Correlation Coefficient < 0.8), we fitted logistic regression equations for each LS with the training samples. Based on the test sample of a LS, regression equations with a meaningful combination of significant, independent factors and the lowest Akaike Information Criterion (AIC) were further evaluated with the Area Under the Curve (AUC) measure of the Receiver Operating Characteristic (Pontius and Schneider, 2001; Swets, 1986). We selected the regression models with the highest AUC values per LS (see results section) and used them in the CLUMondo model to compute the suitability maps for each land system.

2.3.3. Demand and supply relations

The third major component of the model is a parameter set consisting of a list of several demand types on the land and a supply matrix. In the model framework, the demands drive the simulation mechanism and are calculated exogenously in respect to how much of a good (or ecosystem service) is required in total of the study area per year. The supply matrix indicates how much of each demand type (here maize or rice) is produced within a time step by each land system pixel on average across the study area.

In this study, we only consider rice and maize as demand types for simplicity and assume that demands per year equal the crop production statistics between 2002-2016 since the research investigates a process that has already taken place and differences in the balance from imports or exports per crop type were negligible in Sayaboury Province. Hybrid maize is generally not consumed locally but exported altogether to other countries (Thanichanon, 2015). Rice self-sufficiency is culturally important and a reality in Laos since the 1990ies (Eliste and Santos, 2012). We hence assumed that most rice is consumed locally and neither imported nor exported.

In Supplementary Appendix B we explain in detail how we inter- and extrapolated the available records to reconstruct a production timeline for rice and maize (Fig. B1). While rice demand increased steadily, maize demand followed a convex 'boom' curve with a sharp increase from 2005 to 2008/2009 and sharp decrease from 2010 to 2016.

The supply matrix (Table B2 Supplementary Information) was developed based on calculations and integration of several datasets as explained briefly here and in detail in Supplementary Appendix B. In official statistics, crop yields are commonly given for net areas, i.e. under the assumption that all area of a field can be used for cropping. In reality, roads, bare patches, too steep areas and buildings or settlements need to be considered when working at larger spatial scales than field level. Hence, we first calculated gross yields with expert-based, heuristic estimates about how much of the land is usable for cropping on average:

$$Y_g = Y_n \times u \quad 1$$

Where Yg = gross yield (t/ha), Yn = net yield (t/ha), u = factor usable land. Furthermore, land systems contain a certain minimum or maximum share of cropland (cf. decision trees Supplementary Appendix A, Fig. A1 and A2). Therefore, crop coverage needs to be considered for each land system by multiplying gross yields with crop coverage and pixel size to obtain the total productivity (supply) of a land system in tons per pixel (i.e. 100 ha) and per demand type:

$$P_{LS,\,i,t,d} = C \times Y_g \times 100 \quad (2)$$

Where P = productivity, LS = land system, i = pixel, t = time step, d = demand type, C = crop coverage (%), Yg = gross yield (t/ha)

Table B2 in the Supplementary Appendix B shows the supply matrix. Rice production is roughly ten times higher in paddy LS (48 t/pixel) than in rotational LS and mosaic LS (6 and 5.4 t/pixel respectively). This is because the area of secondary vegetation was included in the calculation for rotational LS and mosaic LS. Maize production is about ten times higher in maize LS (105 t/pixel) than in mosaic LS (13.8 t/pixel).

2.3.4. Conversion rules

To complete the basic model parameterization, we defined heuristic, expert-based conversion rules that are elicited in detail, including assumptions in Supplementary Appendix B. First, we built a conversion matrix specifying the possible land system trajectories from one year to another or after a number of years (see Table B2, Supplementary Appendix B). Then we established conversion restrictions per land system indicating the difficulty with which a land system converts to another land system. For example, forest LS face higher conversion restrictions in the model than rotational cropping LS, because forests are more difficult to prepare for agricultural use than in land systems where parts of the land are cleared already or not as densely vegetated. Rotational cropping has low values, signalling that it easily can be converted and reflects the land use policy to eradicate shifting cultivation (Fujita and Phanvilay, 2008). Finally, we specified competitive advantage parameters that define the order according to which the competitiveness of producing land systems is raised in case of land scarcity, i.e. which land system type's transition potential is raised when the demands are difficult to allocate in a simulation year.

2.4. Model experiments

During creation of the baseline model, the following factors were included for maize land systems: market access (travel time to trader company), terrain that is not steeper than 15° (tractors cannot plough beyond this slope) and suitable soil types for permanent agriculture were included (see also section 3.1). After the baseline model was set up, we designed and conducted three experiments with the intention to test the hypotheses, that (i) profitability is more important to farmers in the boom than productivity, (ii) temporal productivity/profitability changes over time better replicate the boom bust pattern than static estimates, and that (iii) higher farmgate prices in a location coincide with the main location of the boom area in southern Sayaboury.

Adopting an iterative, counterfactual approach, we built every experiment based on the results of the previous hypothesis test.

2.4.1. Experiment 1: supply parameterized as productivity versus profitability

Large-scale, geographic land use models are mostly parameterized from the perspective of institutions at national, regional, or global scales, that are concerned with provision and trade of raw commodities by the primary sector in measures of productivity (e.g. tons of a crop/pixel). We set up the supply matrix of the baseline model in this manner. However, as the findings of Ornetsmüller et al. (2018a) suggest, smallholders within the maize boom based their choices on their expectations regarding the income from producing the cash crop maize, i.e. profitability in monetary terms. Computing net return (NR) normally requires to subtract the total costs (TC) from the total gross revenue (TGR) (McConnell and Dillon, 1997). However, data for the total costs of maize production were not available from farmer surveys to the degree necessary. Furthermore the costs are often overlooked by farmers since traders pre-finance seeds, herbicides, tilling, transport and fertilizers and subtract them before paying farmers for their produce. As a proxy for profitability, we hence used total gross revenue and adapted the supply matrix of the baseline model for experiment 1 by computing:

$$TGR_{\,LS,\,i} = P_{LS,\,i,t,d} \times \frac{1}{n}\sum_{i=1}^{n} F_{i,d} \quad (3)$$

Where, TGR = total gross revenue, P = productivity, F = farm gate price (THB/t), I = pixel, LS = land system type, d = demand type

In a nutshell, we multiplied the productivity estimates of the supply matrix in the baseline model by the average farm gate prices per demand type (rice or maize respectively) to arrive at the gross revenue of a land system pixel. We used data from Thanichanon (2015, p. 147) who reports a price of 8 Thai Baht/kg for rice. Based on a map of maize prices in 2013 (Thanichanon 2015, p. 144., see also Figure C.3.1 in Supplementary Appendix), we calculated the average farm gate price of maize to be 4.3 Thai Baht/kg.

The two ways of calculating supply (productivity and profitability) lead to a different ratio between the maize and rice producing land systems. Using the productivity parameters, paddy LS produced half as much as maize LS. Using the profitability parameters (total gross return), paddy LS produced almost the same as maize LS. In both the baseline simulation and experiment 1, the supply matrix was held constant (static) over all modelled years and uniform across the study area (i.e. no spatial differentiation of productivity/profitability of land).

2.4.2. Experiment 2: profitability change over time

Experiment 2 builds on the model parameters of experiment 1 but introduces profitability changes over time, i.e. temporal dynamics in the supply matrix. We changed the assumptions underlying the total gross revenue of maize per year while holding those for rice constant as suggested by the focus group data (i.e. farmer's perception of rice price). Hence, only the total gross revenue of mosaic LS and maize LS changed within the simulation period. Different datasets and studies about the southern part of the province formed the basis for the assumptions on how maize coverage, net maize yields, and farm gate prices of maize changed. Given a lack of data for the northern part of the Province, we extrapolated this 'narrative' of productivity dynamics from the South to the whole study area.

In Supplementary Appendix C, we give a detailed account of the assumptions and data used to calculate the changes in total gross revenue. We also illustrate the timelines of these variables and the overall profitability changes of mosaic LS and maize LS after we implemented these assumptions in the calculations (Fig. C2 4).

2.4.3. Experiment 3: spatial differences in farm gate prices

Thanichanon (2015) indicated that higher prices were offered in Sayaboury town where some middlemen are located and in the southern part of the province where goods are stored and processed for further trade with Thailand. This spatial distribution of maize prices has been mapped by Thanichanon (2015) and we used it in experiment 3, to test how much it influenced the location of the maize boom (see Figure C.3.1 in Supplementary Appendix C). Rice prices were kept constant, given the lack of a comparable map. The maize price map was turned into an index relative to the highest price. This experiment builds on the temporal dynamics already included in experiment 2, only adding the price map to increase the transition potential of a land use conversion towards maize LS or mosaic LS at locations with high price index values.

2.5. Model evaluation

Calibration and validation of the land system model in this study was not possible due to a lack of data that is independent of the data used for model parameterization. This is a common problem and challenge in most land system studies (Brown et al., 2013; Pontius et al., 2018). To still evaluate and know how to improve a model, the most important comparison measurements that are widely used include disagreement due to location and disagreement due to quantity (Pontius et al., 2004; Van Vliet et al., 2016). Since the model purpose of this study is to learn about factors that contributed to the location and quantity of maize expansion, we were only interested in evaluating the land use category 'maize LS'. Ideally, model performance is evaluated with a measure that considers the change of land use between two time steps to assess how accurately the model represents a land change process rather than the land use situation in a single time step (Van Vliet et al., 2011). In our case, there were zero maize LS pixels in 2002 and the result of a comparison of change from 2002 to 2010 equates the comparison of situations in 2010. Therefore, we adopted simple, per category pixel comparison metrics to compare simulation outputs in relation to the LS classification 2010 as the reference map. The map comparison was conducted using the freely available map comparison kit (Netherlands Environmental Assessment Agency, M., 2011).

3. Results

In this section, we present our findings on the factors that contributed to the spatial pattern of the maize boom in Sayaboury Province. Key results of the logistic regression are presented in Fig. 3 and Table 2. The main findings of the experiments are presented in Fig. 4 and Table 3.

3.1. Logistic regressions and location suitability for maize land systems

A combination of three location factors yielded the strongest, meaningful regression for maize land systems in 2010 (AUC value 0.83): travel time to maize companies (market accessibility), slopes flatter than 15 degrees (i.e. ˜27%) and soil types that are suitable for agricultural use. In Sayaboury Province, local traders arrange the transport of inputs and harvested products to and from the farms or village centers. Hence, the travel time to the maize companies served as a proxy to represent the costs of transport for a local trader and therewith the reach of a 'market opportunity' for the farmers. However, the area that can be cropped intensively with maize is limited by slopes that are too steep for tractors to operate. Also, there are soil types which are not favourable for arable agriculture, but the ones characterized as suitable in the study area were Cambisols and Luvisols. According to the results of the logistic regression, these three location factors indicate areas in the South and Centre of the Province as generally suitable for a maize boom to emerge (Fig. 3). These areas cover a larger area than suggested as maize boom area in the LS classification 2010.

Outcomes of the logistic regression and AUC values are shown in Table 2 and ranged from moderate (0.69) to excellent (0.92) goodness of fit.

3.2. Simulation experiments

Beyond examining the significance of location factors, the land system model was used to test the influence of further causes underlying the location of the maize boom in three experiments of which the findings are shown in Fig. 4 and Table 3 and explained in the following sections.

3.2.1. Effects of supply parameterized as productivity versus profitability

Experiment 1 tested the hypothesis that profitability is a more important decision factor to engage in the maize boom than productivity (a parameter used in many large scale land use models). Consequently, using profitability in the supply matrix should more closely match the maize boom pattern of the reference map (LS classification 2010). The results show a smaller location disagreement of 42% in experiment 1(profitability) versus the baseline model (productivity) with a larger location disagreement of 55%. Hence, using total net revenue as a proxy for profitability slightly contributed to explain the location.

In both the baseline model simulation and experiment 1, agricultural areas for paddy, maize and mosaic LS have expanded widely and rotational cropping almost disappeared. However, this is an extreme overestimation of agricultural expansion when compared with the LS classification 2010. With an overshoot of 1887 cells and 1663 cells respectively (false positives), both the baseline and experiment 1 allocated more than twice as much maize LS than present in the reference map (995 cells), whereas the parameterization with profitability again performed slightly better. Overall, experiment 1 yielded the worst quantity fit but the best location fit.

3.2.2. Effects of profitability change over time

Given that quantity disagreement was high, i.e. expansion of maize LS was strongly overestimated in the baseline model and experiment 1, we tested in experiment 2 how large the effect of accounting for temporal changes in profitability of maize-based land systems (maize LS and mosaic LS) would be. The experiment included that total gross revenue increased due to rising prices and yield improvements based on new machinery, new cultivars and herbicides in the first years of the boom. Then, total gross revenue slightly declined due to falling prices and lower yields because of land degradation in the later years.

Overall, this resulted in limited agricultural expansion and rotational cropping LS remained more widespread in the northern part of the province. More specifically, including productivity dynamics in the model lowered quantity disagreement to a large extent. Instead of overestimating the amount of maize LS cells by 122%, experiment 2 even slightly underestimated maize expansion with a quantity deviation from the reference map of -17%.

While this experiment resulted in a closer match of quantity of pixels (i.e. size of maize boom area), the pixels were more widely scattered across the study area instead of focused in the South (see lower panel of Fig. 4). With 82%, the location disagreement doubled in

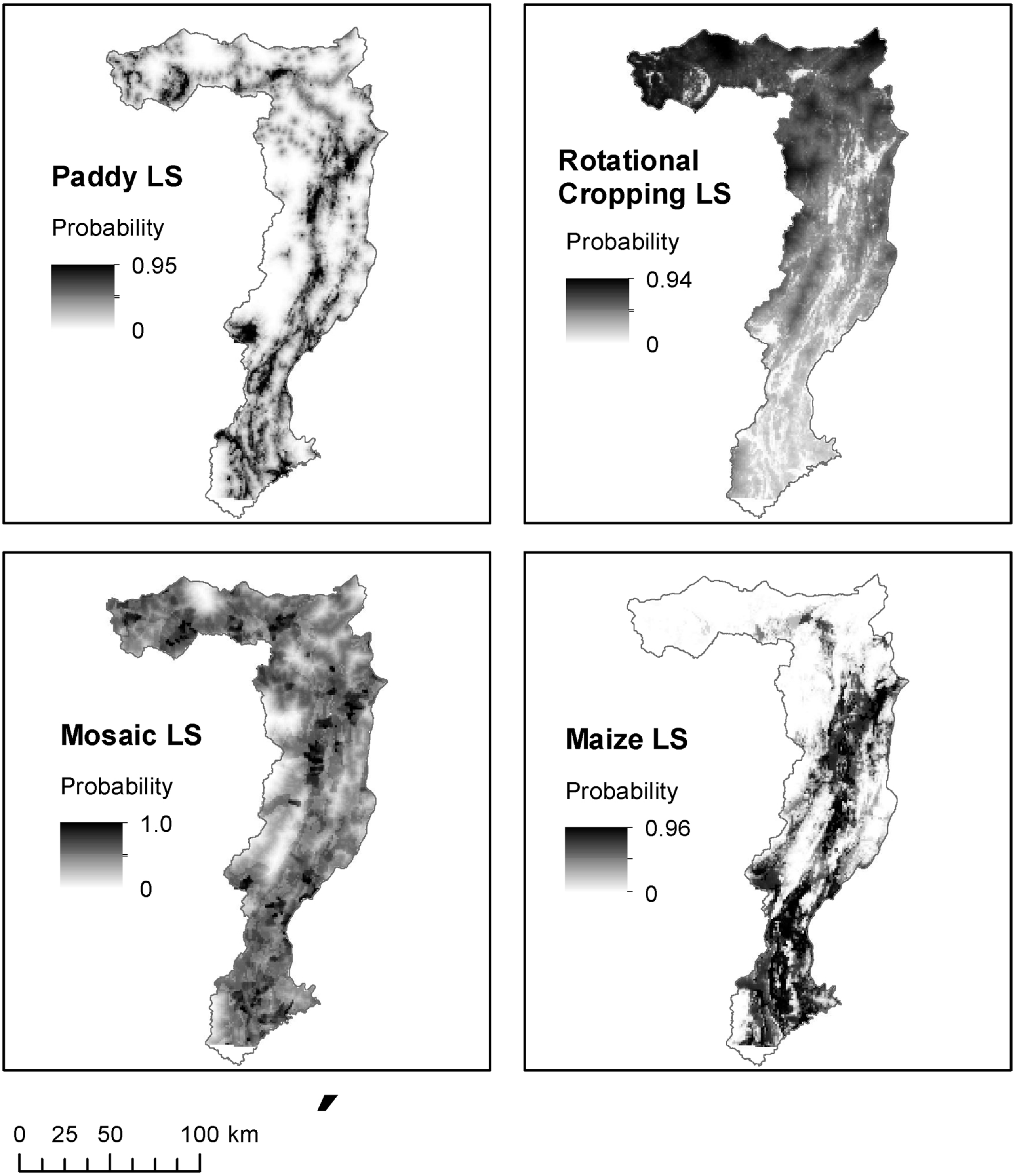

Fig. 3. Suitability maps indicating the probability to find a land system at a given location. Homogenous probability across the province was assumed for Forest LS.

comparison to experiment 1 (Table 2). Overall, experiment 2 yielded the best quantity fit but the worst location fit.

3.2.3. Effects of spatial differences in farm gate prices

We tested in experiment 3 whether incorporating the spatial pattern of farm gate prices would improve the location fit of maize LS. The map we added reflected higher maize prices in the South of the province and increased the location specific probability of a pixel to turn into a maize producing land system (maize LS or mosaic LS).

The simulation output of experiment 3 showed an overall pattern similar to experiment 2 with fewer mosaic LS and a slightly better location overlap with the reference map. The location disagreement of maize LS slightly decreased from 82% (experiment 2) to 74% (experiment 3) while the amount of maize LS cells was overestimated again (+25%). Yet, this overestimation turned out much more mildly than the baseline model and experiment 1 and experiment 3 is the best compromise of location and quantity fit of all simulations. Despite this, a large location disagreement remains and further tests and/or improvement of the data used in this study are necessary to find a combination of factors that explains the location and cluster of the maize

Table 2
Logistic regression models per land system (LS). P values of significance: 0 '***' 0.001 '**' 0.01 '*' 0.05.

Land System (dependent variable)	Intercept	Coefficients	Independent variables	AUC value
Paddy LS	−0.1886	3.1464 **	Flat terrain (< 3° slope)	0.9268
		-1.3014 **	Travel time (tt) to village center on national roads	
Forest LS	−0.5	0	Assumed to occur everywhere with same probability	–
Rotational Cropping LS	−1.84209	0.35854***	Travel time to border checkpoint on all roads	0.7861
		-3.54761**	Flat terrain	
Mosaic LS	−0.188697	0.022955***	Population density	0.6926
		0.546539**	Less suitable soils	
		-0.748496***	Travel time to villages on all roads	
Maize dominated LS	1.6211	1.7642*	Suitable soil types for permanent agriculture	0.8364
		-4.0538*	Steep terrain (≥15° slope)	
		-1.6274**	Travel time to maize trading company	

boom in the southern districts of Sayaboury.

In summary, the model helped to examine the role of a number of factors that contributed to the maize boom in Sayaboury Province, yet couldn't fully explain it. Market access represented by the proxy travel time to trader companies, slopes that are not too steep for tilling with tractors and suitable soil types were found to be a significant combination in the logistic regressions. Through the model simulation experiments we learned, that representing a bottom up way of thinking about land productivity in terms of profitability improves land use model performance. Moreover, temporal changes in profitability with associated technological changes (ploughing, chemical inputs, etc.) had the strongest effect in explaining the spatial extent of the maize boom. Taking into account spatial differences in farm gate prices did lead to a slightly better location fit. However, whilst those economic and geographic factors tested throughout this study all contribute explanations, they are still insufficient to fully explain the spatial pattern of the maize boom that occurred in Sayaboury Province in Laos between 2002 and 2016.

4. Discussion and Conclusions

This study constitutes an attempt to formalize knowledge about crop booms within a land use model and create a synergy between land system science and political ecology (Lestrelin et al. 2013). To advance our understanding of causal effects of different factors, we tested successive hypotheses in a stepwise model building process. While the results suggested that economic and geographic factors such as market access, profitability, soil, slope, technology that increases profitability over time and spatial differences in farmgate prices partially contribute to explain the boom, a full explanation has not been found. In the following sections, we first discuss our findings in relation to existing work on crop booms. Then we reflect on data and modelling issues and finally we outline implications of the findings for policy with suggestions on how to prevent or react to crop booms.

4.1. Explaining the spatial patterns of the maize boom

The baseline model version and the three experiments include a factor combination of slope, soil types suitable for agriculture and market access (proxy: travel time to (or accessibility of) trader companies as explained in section 2.1. Study area). Among other,classic geographic factors these were used in many land use models to calculate probability maps for different land use types. Using accessibility of trader companies instead of general accessibility to settlements, border checkpoints, district or province capital is novel because it more specifically mimics the market accessibility of contract farming schemes for the boom crop. According to Cramb et al. (2015) contract farming schemes are a key factor for crop booms because in these arrangements the traders provide both the upstream inputs such as seeds, herbicides or fertilizers and the downstream services such as transport and marketing of the harvested goods. The results of the logistic regression calculations underlying the land use model suggest that travel time to trader companies is the most significant factor and hence confirm the essential role of contract farming schemes as the market access for farmers. On top of that, the results of the baseline confirm another argument of Cramb et al (2015), that more is necessary for a boom to emerge (e.g. social dynamics) than the biophysical (soil, slope), and economic factors (market access, total gross revenue, spatial differences in farmgate prices of the boom crop) we tested in this study.

Most large-scale land use models are designed to answer questions of institutional interest, that is concerned with broader socio-economic goals such as trading or food security. Applying insights on farmer's decision making from Ornetsmüller et al. (2018a), we tested their statement, that a stark contrast of profitability in comparison to alternative crops or land uses is a major incentive to adopt and pursue 'boom cropping'. The results of the baseline model and experiment 1 confirm this as our model performed better when using profitability of the boom crop (proxy:total gross revenue) as compared to productivity (crop yield). However, both versions still overestimated the quantity of the maize boom area by more than double the amount identified in the reference map (i.e. land system classification 2010).

The early 2000s were a time of much political-economic and legal support in Sayaboury Province that fostered technological change. This included increased net yields of maize due to new cultivars, herbicides and fertilizers which at the same time helped reducing labor effort with machinery to till the land, plant more effectively and transport and process maize harvest (Thanichanon, 2015). Over time, this made intensive maize mono-cropping disproportionally competitive over other land uses. To reflect the technological changes and related increases of profitability of maize mono-cropping within the boom years 2005-2009/10, we turned the static parameterization of productivity into a temporally dynamic one in experiment 2. Following this, the quantity disagreement dropped extremely between experiment 1 and 2 and more closely resembled the reference map regarding the size of the boom area (sum of maize LS pixels). Hence, we conclude that technological innovations such as ploughing increased productivity and profitability, which made it possible for the amount of maize demand to be produced in a delimited area of the province (southern districts mainly). This corresponds with Byerlee's (2014) work, who finds that crop booms are enabled by local political economic measures that are biased towards a certain stakeholder group, or – as we have learned in this study – towards a certain form of land use.

All studies on crop booms mention the lucrative, high commodity prices as essential triggers for the boom process. We tested in experiment 3 whether the spatial pattern of farm gate prices would significantly explain the spatial pattern of the maize boom. This refinement of the 'incentives' and profitability of higher prices in the southern part of Sayaboury Province explained the spatial pattern slightly better but not yet fully. We conclude that, beyond the economic and geographic variables tested in this study, there must be further factors (as suggested in section 4.2) that explain the clustered emergence of the maize boom at specific locations.

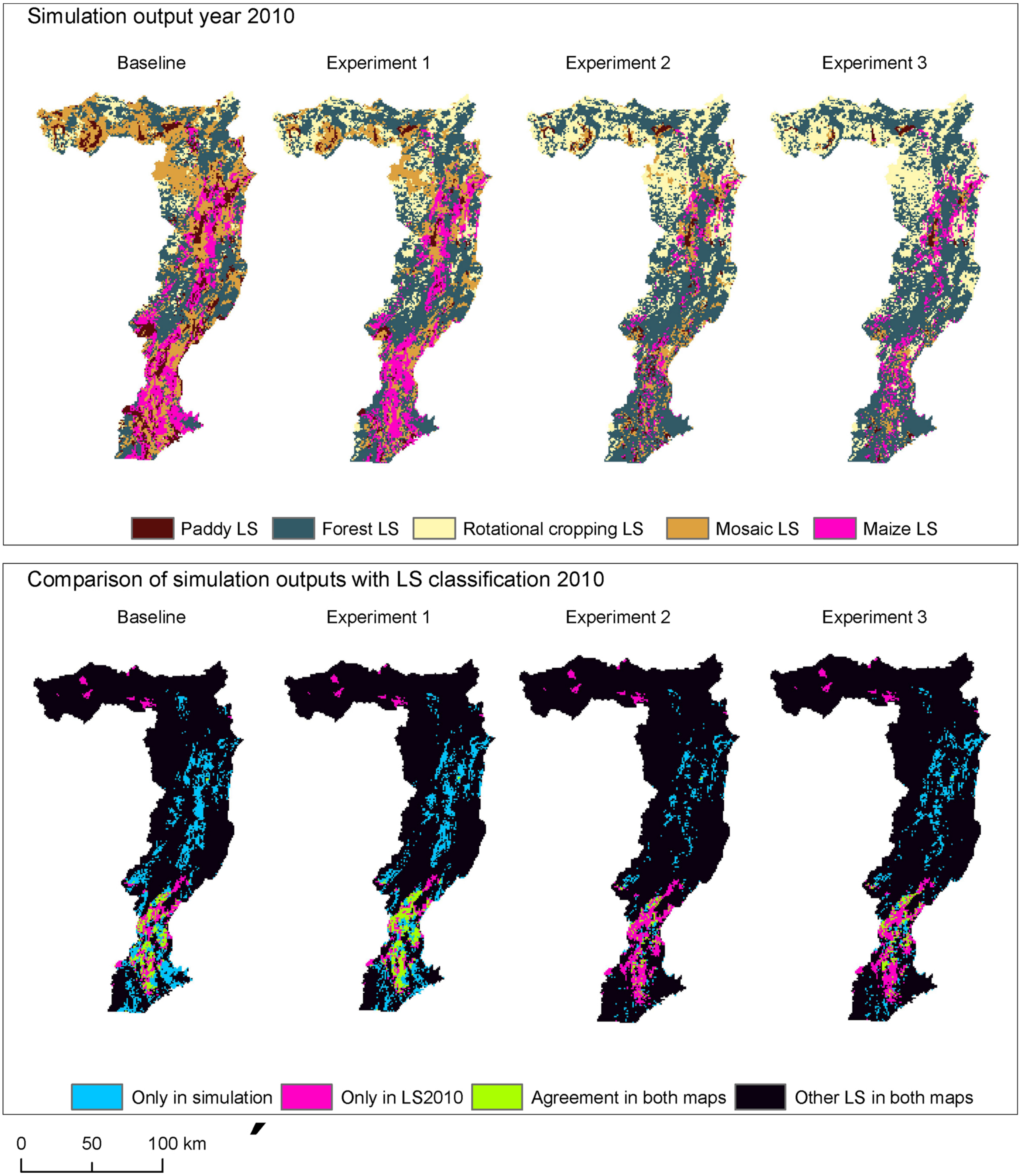

Fig. 4. Results of model simulation in year 2010 (above) and map comparisons showing in which areas the respective simulation output agrees or disagrees with the LS classification 2010 (below). Baseline = institutional view on productivity with mass of harvest, experiment 1 = farmer's view on productivity with profit/total gross revenue, experiment 2 = productivity changes over time, experiment 3 = spatial pattern of farm gate prices.

4.2. Methodological advances and constraints

Modelling a system transformation or regime shift from a subsistence to a commercially oriented agrarian system brings up many challenges and requirements for data and processes to be represented in a model. Data limitations restricted model parameterization, spatial calibration and validation in this study. This implied that many assumptions and interpolations were necessary to investigate the research question(s). To account for this, we carefully conducted a step-wise approach, tested assumptions that were used in the parameterization of the model and cross-checked key parts such as the productivity-demand relations by triangulation with data or literature. However, it remains a study with imperfect data inputs and only a selection of processes that could be represented. This study is therefore subject to a number of limitations.

The major limitations of input data concern the lack of spatially

Table 3
Measures of comparison between model simulations and LS classification 2010 as the reference map.

	LS classification 2010 (reference)	Baseline model	Experiment 1	Experiment 2	Experiment 3
Total # of pixels of category 'maize LS'	995	2337	2212	825	1242
True positives (agreement both maps)	995	450	579	175	262
False positives (only simulation)	0	1887	1633	650	980
False negatives (only LS 2010)	995	629	500	904	817
Disagreement due to location (# pixels)	0	545	416	820	733
Disagreement due to location (%)	0	54.8	41.8	82.4	73.7
Disagreement due to quantity (# pixels)	0	1342	1217	−170	247
Disagreement due to quantity (%)	0	134.9	122.3	−17.1	24.8

explicit production costs of maize and alternative crops to move from total net revenue as a proxy to conventional profitability estimates. Other data issues apply to the land cover/land use maps as part of the land system classification, key explanatory factors and productivity measures. First, the land cover datasets used within the land system classifications 2002 and 2010 were the best available data to reflect the land use changes in Sayaboury Province for the spatial extent and temporal requirements. However, the slightly different thematic classifications between the two dates do not allow for drawing conclusions on land use developments related to forests or paddy areas. Therefore, this study is focusing only on the expansion of maize LS during the boom period. Second, poverty and land governance as two broad contextual factors could not or only partly be included. The differences between Thailand and Laos in terms of poverty levels are very likely a strong contextual factor, but this relationship could not be explored because the spatial extent of the modelled area is smaller than the area in which this wealth differences appear. We suggest to test this with a model application of larger spatial coverage. Land governance themes, such as the disadvantaged land rights for shifting cultivation were partly represented in the conversion resistance estimates. If spatial differences in the quality of land governance and land administration were to be included, this would first require the production of respective spatial assessments. Third, some factors are represented static in the model even though they changed during the boom and bust. The two most notable variables are used for the accessibility datasets and consist of the road network that represents the situation of 2011 and the location of trader companies. In reality, the road network improved and densified in time and the network of trader locations represented by data of 2013 had not been there at the beginning of the boom. Finally, given the large influence of productivity and profitability measures, the extrapolation of estimates from the South to the whole province and the lack of data on production costs may have led to an overestimation of maize LS pixels in the North and in general. A time series reflecting the spatial diversity of productivities and profitability in comparison to other income and crops would help estimating the corresponding uncertainty.

Productivity changes are part of an incremental process and explain a large part of the magnitude of the boom. This means, model projections based on static productivity parameters overestimate the expansion of intensive agriculture.

We see several ways to further study crop booms using land use models by data collection for the shortcomings mentioned above and inclusion of further processes. A part of the missing factors are possibly heterogenous and could be examined in further studies, given that data could be acquired. Another part may not be possible to represent in a land system model with empirical data, such as the factor 'trust of a farmer' into the reliability of a trader within the farming contract. Factors that are rather homogenous within this study area (e.g. poverty, land governance) may very well be heterogenous if the spatial extent of the study are would be enlarged e.g. towards the whole region of Mainland Southeast Asia. Social processes, including imitation behaviours, could be investigated for example by testing the effect of different land use conversion rules for neighbouring cells to mimic imitation behaviour. Cultural ecosystem services provided by rice producing land systems would be another interesting avenue to explore, since rice self-sufficiency is an important value in the Lao culture. Finally, looking more closely at the bust phase would require to include land degradation as a feedback of too intensive maize cropping after several years. However, the relation between decline of soil fertility and decline of yield for maize farmers in the tropics are not well enough established in current research (Bruun et al., 2017).

Comparable, spatially explicit studies on crop booms in other parts of the world are limited. Yet, several studies offer a brief comparison. Ramankutty and Coomes (2016) used the lens of land use regime shifts to explore historical crop booms such as two, large soy expansion phases in Brazil in the early 1970ies and late 1990ies for which the triggers and preconditions were different (climatic stress events in the USA, and international trade and policies for soy as fodder from the EU), but the self-reinforcing mechanisms of soy expansion and intensification were both related to political-economic investments in infrastructure, subsidies for credits and technology, and political power of lobbyists (Ramankutty and Coomes, 2016). The 'Green African Revolution' of maize has had ups and downs, but generally maize in Sub Saharan Africa is reported to have been adopted widely as a staple crop given appropriate technologies and policies in the 1980ies (Smale et al. 2011). At the same time Smale et al. (2011) attest a large area in Sub-Saharan Africa being suitable for maize cropping but access to markets, finance and technology is limited for smallholders. Less successful was the cash crop jatropha, an oil crop in a hype for biofuel in Southern Africa. Promoted widely with too high expectations on yield and too little agronomic knowledge it was adopted as wonder crop by smallholders and large plantations but soon failed and was abandoned due to too low profitability (Maltitz et al., 2014). These flashlights into the crop boom literature outside of Asia showcase that there are several commonalities (profitability, role of policies, market access), however, a more in depth global review or meta-analysis is still due.

4.3. Implications for policy

The findings of our study offer valuable insights for governance bodies around the globe that try to both stabilize forested areas with associated biodiversity and at the same time foster economic growth of an agrarian society. Experience of several crop booms has shown that having smallholders seize opportunities of high commodity prices by enabling more effective technology does not automatically lead to a sustainable future for those smallholders. Instead, when expecting or struggling with crop booms, it may be useful for a governance body to examine whether boom crops are incentivized by technological innovations (e.g. ploughing with tractors, herbicides, chemical fertilizers) that favour mono-cropping over other, less exploitative land uses (e.g. agro-ecological farming) particularly in mountainous areas and locations with easily erodible soils. In case disproportional conditions are identified, a regulatory framework should be put in place to make less exploitative land uses more competitive again and raise awareness about the socio-ecological disadvantages of crop booms.

Declarations of competing interests

none

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Appendix A. Supplementary data

Supplementary data associated with this article can be found, in the online version, at https://doi.org/10.1016/j.envsci.2019.04.001.

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